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A Semi Smart Adaptive Approach for Trash Classification

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Abstract

Waste management and recycling play a crucial factor in world economy sustainability as they prevent the squander of useful materials which can lead in garbage landfill reduction and cost reduction respectively. Garbage sorting into different categories plays an important role in recycling and waste management; but unfortunately, most garbage sorting still depends on labor which has a reverse impact on mankind and world economy, so there are different approaches to replace human separation by intelligent machines. In this article, we propose a comprehensive approach, Semi Smart Trash Separator to classify garbage and trash using the following technique: pre-cycling by assigning a barcode or QR code to each material, which will enable the separation process as per assigned code; Magnetic separator helps in collecting conductive metal, then the non-conductive materials are classified according to their hardness. This test is a unique idea used in trash classification. Finally, if there is ambiguity in waste material classification barcode or material properties, the classification will be done using neural network techniques depending on the shapes of trash. Mat lab software is modified to handle convolutional neural networks in the image recognition (AlexNet and GoogLeNet) to be used in the trash classification processes and to test their accuracy. The tests are performed using a trustable data set. The material recognition accuracy rate from the obtained results on AlexNet and GoogLeNet are 75% and 83% respectively.

Keywords: Artificial Intelligence, convolutional Neural Network, Machine Learning, Neural Network, Semi Smart Trash Separator.

1 Introduction

The increase in population and the development of the industrial revolution that the world witnessed in the past decades contributed in an alarming way to the pollution of the environment. The population reached more than 7.7 billion in 2019 [1], and the population is also expected to increase rapidly in the coming years, which in turn will lead to more industrial and human waste that will negatively affect the environment and economies of countries [2]. Environmental scientists and researchers have invested in research and studies of waste disposal management, and the creation of new business models concerned with the transformation , reuse and recycling of materials in the concept of life cycle, as presented in Figure 1.

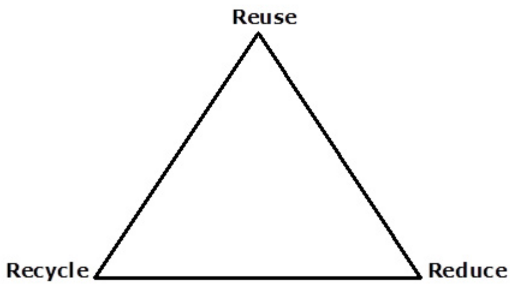

Figure 1: Conceptual frame definition for circular economy

Several strategies were developed and assigned to handle household, industrial, and wild-live waste through material reuse and recycling to reduce waste [3]. Waste management cycle starts from garbage collection, transportation, and treatment according to environment authority regulations. Much research was done to address waste and garbage collection as many countries experience exhausted waste collection services and inadequate management features [4]. Garbage collection is a severe problem for poor developing countries since garbage is scattered over vast areas, causing a non-efficient method to collect and dump waste [5]. Waste sorting is still the critical stage for recycling in different countries especially industrial ones like the United States [6].
Garbage materials are classified into the following categories: 5.8% metals, 3.5% glass, 16% plastic, 12.9% papers, 1.8% textiles, 53.7% biodegradables and the remaining landfills waste [7]. It is clear from the material classification, that most of the waste materials are Biodegradable. These are composed of food waste, garden waste, restaurants, caterers and retail premises which are considered the big challenge for the municipal solid waste management systems [8]. Plastic garbage materials is another crucial aspect in solid waste management, so many efforts were done to handle plastic waste due to: the plastic impact in the global economy, the low material recovery rates, plastic disposal methods and the increase size of plastic production which is expected to exceed 1600 million tons per annum (Mtpa) in 2050.
Plastic materials are used in different applications including packaging, medical devices, building, textile, consumer goods, transport, construction sectors and others [9][10]. Plastic packaging is considered the largest production ratio compared to other production sectors as presented in Figure 2.

Plastic materials have undesired effects on environmental pollution as it is expected that plastic waste disposed in oceans will be three times the number of fish by 2025 [11]. Thus, this is a terrible problem which will affect the aquatic life and increase the environmental pollution. Plastic is not a problem by itself, but the methods used to get rid of plastic is the main confliction. Plastic takes a long time to decompose; for example, the plastic bags takes from 10 to 1,000 years to decompose.
The average decomposition rate as shown in Figure 3, through the years for different types of materials [13]. Sanitary pads and monofilament fishing lines need a longer time to decompose, so there is a vital

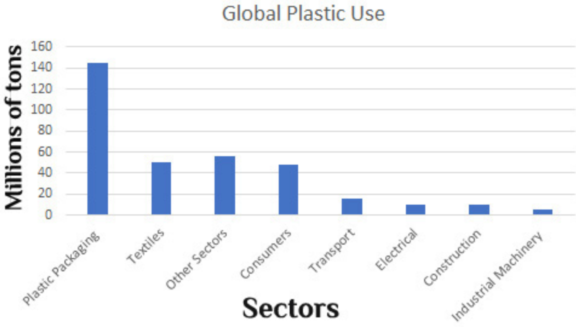

Figure 2: A Comparison weight in million tons for different global plastic use [13]

need to handle waste classification management using the new technology aspects in optimal manner, hence the idea of this research paper is born.

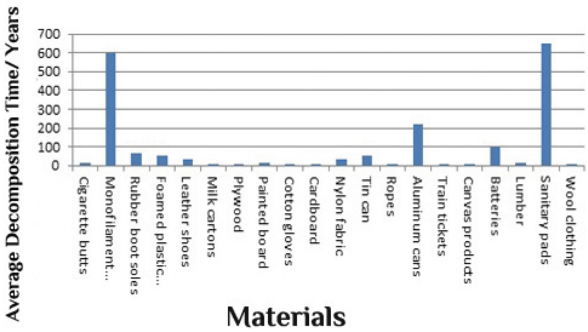

Figure 3: The average of decomposition rate for different Material in years

To tackle the environment problem of plastic waste, several researches had been conducted, depending on the plastic production cycle which starts from the production to the consumption and finally plastic waste management as shown in plastic life cycle Figure 4. In plastic production, plastic is controlled by its physical properties and are classified into two types: thermoplastic, which can be recycled using reheating and thermoset which cannot be recycled through reheating [14]. Plastic use reduction and optimization can be regulated through governmental regulations such as restrictions and taxes, so developing countries must follow the experience of developed countries that are known for plastic production, use and plastic recycling strategies [15]. Several researches and studies were done on determining the position and concentration regions of plastic waste to optimize waste collection and transportation through utilizing the benefits of new technologies such as GIS technology which is updated frequently [16].

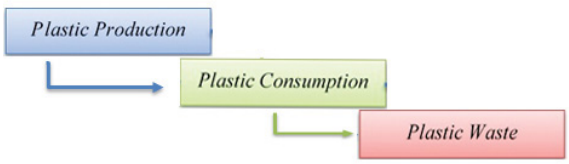

Figure 4: Plastic life Cycle

Since plastic industry is very important for the global economy, mankind can benefit from plastic waste management and increase the opportunities for innovations and jobs creation. Recycling and waste management of garbage materials is now considered as most important need to control the undesired effects of plastic disposals. Garbage segregation and recycling is a markable solution to reduce the environmental pollution and minimize the resource's cost of waste management; as a result of this, many researches are done to reduce the undesired effects of garbage pollution. In this paper, the authors developed an approach to find effective solutions to solve the mentioned problems. Garbage waste auditing is considered as one of the main challenges for public health priority, as it is done starting from waste generations, followed by the study of the waste boundaries which are weighed and catalogued with respect to waste segregation process [17]. Recycling process which is developed and agreed on by local vendors and recommended to consumers. It consists of two major stages; Pre-process recycling which can be done before waste disposal and separation processes by classifying the trash according to certain categories (i.e. plastic materials, paper materials, metal materials, etc), and Post-process recycling which is done during garbage and waste landfill. Unfortunately, most of the world countries use manual recycling centers which depend on human resources to sort waste leading to a high risk of catching diseases. Automatic techniques are proposed to facilitate the recycling of the correct trash for each garbage sets. One of the proposed schemes to separate garbage is to use PIC microcontroller-based garbage separation model. This model uses a smart robot that is able to separate degradable and non-degradable waste by applying image processing techniques [18]. Image processing is used to classify the garbage by taking an image and classifying it to four categories: paper, glass, metal, and plastic. In this research, model deep learning and artificial intelligence were applied depending on a database which includes about 400 images for each classified category and different model experiments using Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random, AlexNet, Forest (RF), (VGG16), and Pre-trained VGG-16. According to the obtained results from these experiments, it was found that the VGG-16 method is the best approach as its accuracy reaching 93% for the tested scenarios [19]. Extracting the good part of the generated garbage in large cities to be recyclable is needed to find or apply reusable methods that could bring benefits or at least reduce environmental problems. The existence of techniques or models which allow people to recycle or sort garbage has become important in the correct disposition of those materials. There are many types of recycling categories, but people still can be confused or are unable to properly recognize and determine the correct trash bin to dispose of each type of garbage to be used in recycling. In order to reduce the impact caused by the incorrect disposition of garbage, more specific domestic (i.e., paper, plastic, glass and trash), as many studies were done to segregate the disposed garbage as explained before. We proposed to use an automated system based on image processing and convolutional neural network techniques to utilize correct separation of waste within recycling categories. Most of the world countries still depend mainly on humans' ways or labors to manage solid waste. despite this, there were many attempts done to move and transfer to automatic ways. Since, population and industrial growth are considered the main factors in garbage production, so there should be effective solutions to manage waste [20]. Waste management and efficient sorting techniques are essential to our ecosystem. It is essential for the society to reduce waste accumulation by recycling and re-using the dispose of certain products; since the available land for living has begun to shrink resulting in impossible solutions to obtain proper landfill. Efficient elective sorting is often implemented to improve recycling, reduce the amount of disposal garbage, and reduce the negative impacts on environment [21]. Waste segregation and classification are vital processes in waste management, waste pre-classifying and post-classifying using the available technologies are very important to reduce the amount of garbage in the landfill [22]. In this paper, automated post- classification and segregation is proposed as an effective solution to reduce the amount of waste in the landfill, the proposed approach is based on three stages as described in the next sections.

2 Waste Classification Proposed Approach

Several studies have been conducted to develop new technologies and smart solutions in waste sorting and classification to reduce the overpopulation and the Industrial Revolution problems i.e. (reducing the workforce, enhancing the beauty and health of cities, reducing noise, reducing fuel consumption, and achieving the sustainable development by using green technology [23].

Nowadays, most of the cities in developing economies start to adapt pre-classifying or sorting of waste through handling designated waste containers according to the type of waste. for example, metal containers to collect metal waste, paper containers, plastic containers and so on. In this paper, materials barcode is assigned for any used material, this barcode will be used in the automated sorting as the first step in the waste materials classification or sorting proposed approach, then magnetic separation process is used to classify waste material into metal or nonmetal materials. after that, a hardness test is used to classify the non-metal materials according to the Durometer Hardness Test values. Finally, convolutional neural network is used to classify the undefined or not recognized materials according to their shapes depending on a large data set of images as shown in Figure 5.

3 Classification scenario of waste material

The main conflict of waste classification and sorting arises when; The materials that are consumed and disposed in litter containers which results in different materials of garbage and toxins being mixed and assorted, all together as waste and detritus. This makes it difficult to sort, classify and recycle. Therefore, there is a need to establish a post-classification or sorting of waste materials and this will be done according to the proposed approach. The proposed approach uses a Semi-Smart Trash Separator (SSTS) prototype that is a hybrid approach between barcode, magnetic separator, shore hardness, and convolutional Neural Network (CNN) algorithms. The smart multimedia image classification technology is done by convolutional neural network image classifier that using deep learning convolutional neural network for image classification. (SSTS) prototype is handled according to the following stages:

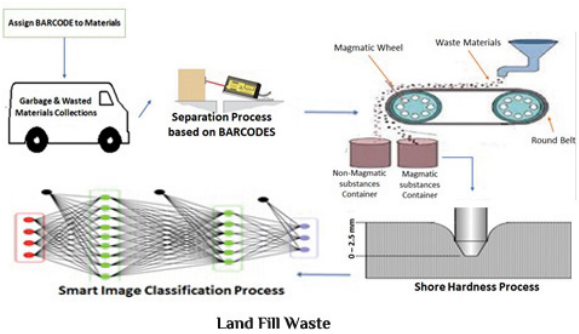

Figure 5: Semi Smart Trash Separator proposed approach

3.1 Barcode Separation:

Barcode or QR codes can be used as the earliest separation stage to enhance waste management systems as there are many researches done to use barcode and QR code with RFID to mimic the trash containers in order to improve waste management processes through enabling smart locally sorting [24]. Here, in this research we are assumed that garbage containers are not smart, so when waste material or garbage are collected by Municipalities' trucks and sent to the landfill, the separation barcode or QR will be used in the separation process, and if the code recognition fails then the proposed approach will be shifted to the second separation stage (i.e the magnetic separator) as it is explained in SSTS flow diagram Figure 6.

3.2 Magnetic Separator:

Magnetic separators are used to separate ferrous materials in waste sorting process; all materials with ferrous traces will be separated and sorted. Such materials are castings of Aluminum, Nickel, Cobalt and Iron. Nowadays, electromagnetic separators are used; these electromagnets efficiently remove ferrous metals in heavy industrial applications like coal, limestone, sand and other aggregates. Since, not all the materials are ferrous materials; the magnetic separator will not be able to separate effectively the waste materials; as a result the authors propose to use the hardness test to classify the waste materials, and according to their knowledge no researchers proposed this idea in waste material separation. A complete description of hardness separation is explained in the following paragraph.

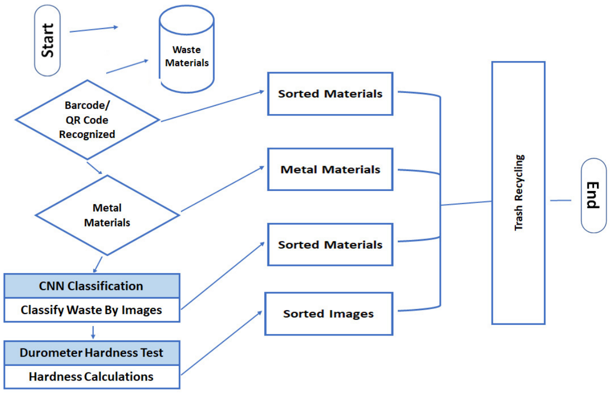

Figure 6: Semi smart trash separator stages

3.3 Hardness test:

The shore hardness is a measure that describes the resistance of a material to penetration of a spring-loaded needle-like indenter [25]. It is used to represent the resistance of non-metal materials to the penetration of a conical indentor, so when there is a full penetration then the hardness value equals to zero, and when there is no penetration the hardness value is equaled to 100. The value of shore hardness is used to classify materials for example: Shore A scale is used as a measure for soft Elastomers materials such as rubbers, and other soft polymers. While, Shore D scale is used as a measure for hard elastomers and most other polymer materials (Thermoplastics, Thermosets) hardness as it is depicted in Figure 7 and Figure 8 respectively.

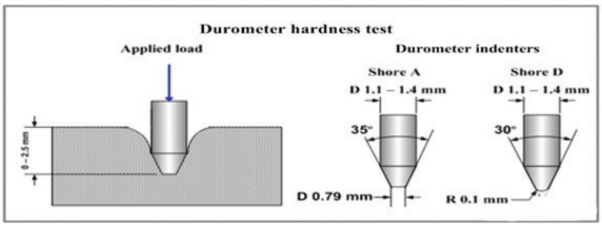

Figure 7: Soft material durometer hardness test

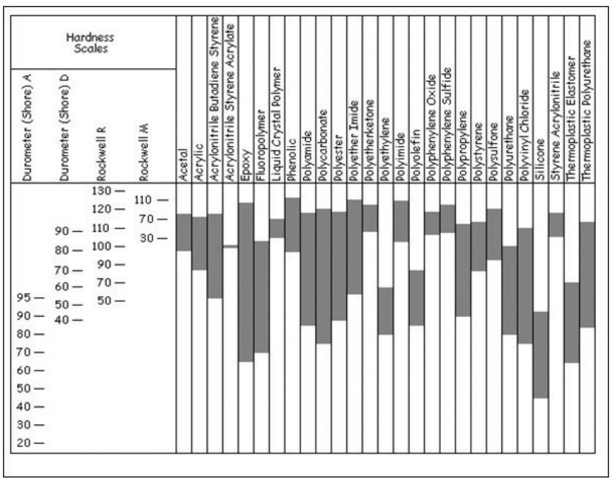

Figure 8: Hardness comparison chart

Some waste materials are composed materials, so there is a challenge to classify them according to ferrous and non-ferrous, in addition to that, their hardness value may be difficult to measure and compare, also the barcode and QR code may be not clear or does not exist at all, so we propose to use artificial intelligence and convolutional neural networks to classify the waste materials according to their images as depicted below.

4 convolutional Neural network for image classification

Artificial Intelligence (AI) and Machine Learning (ML) algorithms are powerful tools that facilitate, and grant intelligence to computers enabling them to do some of the human activities such as making decisions based on discovering relationships among the data, these decisions allow systems to adapt to certain conditions and are applied in many devices and technologies such in smart houses, smart grid, smart meters, smart traffic lights and so on [26][27]. Despite the uses of intelligent system to emulate the human sensory responses including vision and speech, Human-level satisfaction is still not achieved [28]. Convolution Neural Network (CNN) is considered as one of the most effective deep learning techniques used to test the accuracy of image recognition for a large number dataset [29]. CNNs are applied in image recognition, image segmentation, features detection that are widely used in medical applications, and different industrial tasks which resulting in their success beyond academia [30], [31],[32]. As an example, High Tech companies such as Google, Microsoft, ATT, NEC, and Facebook, have established Research centers to explore CNN architecture. Recently, deep CNN based models were employed for image processing by front runner companies [31] [33]. Unfortunately, when the trash images are captured by the camera, they suffer from redundancy and some obstacles related to image scars, dryness, and moistness that lead to problems in image classifications; so to overcome these obstacles images need to be preprocessed using image enhancement techniques such as Normalization, Filtering, Noise reduction, Binarization, and Thinning. In this research, we apply Binarization, and Thinning to enhance and increase the accuracy of trash image classification.

4.1 Binarization:

It is used to enhance image classification through separating the image features and objects from their background. In this research, **imbinarize(***I)* function using MATLAB was developed to generated binary image from 2-D or 3-D grayscale image I, then all the generated values are replaced to determine threshold with 1s and set all remaining values to 0s. imbinarize function implements **Otsu's** method, which assigns the threshold value to minimize the intraclass variance of the thresholder black and white pixels [34]. Imbinarize functions implements a 256-bin image histogram to determine Otsu's threshold. The image set features (**f**) is calculated based on the following equation to transform feature f into a binary feature representation [35].

$$(\mu i) = (1/n) \sum_{i=1}^{n} (f\, j,n)$$
$$\textbf{where } fj \subset (-\infty\ ,\mu i) \text{ - } (\mu i\ ,\infty)$$

4.2 Thinning:

It is also used to enhance image classification through implementing thinning algorithms. This is done by taking a binary image of a trash and making the ridges which will appear in the print as one pixel wide without changing the overall pattern, then gaps are left in the ridges to create an image "skeleton", so this will facilitate determining features and eliminate the redundant data [36].
In this research, we choose AlexNet and GoogLe Net in trash image classification; as these are considered the most effected models for deep learning image recognition networks, and they have competed successfully in the ImageNet Challenge [35].

5 Trash Image Classification

5.1 AlexNet:

CNNs starts digits recognition by LeNet and at that time, CNN was unable to handle all scale classes of images [37]. AlexNet is one of the effective deep CNN architecture tools; due to its fast processing capabilities and low computational time cost [38]. AlexNet showed superiority results in image classification and recognition tasks. AlexNet was modified to handle new features in image classification to develop the capacity of CNN to perform deep recognition strategies through implementing several optimizations parameter [39]. AlexNet was trained in parallel on two NVIDIA GTX 580 GPUs to overcome the hardware capabilities limitations [11]. In AlexNet, the feature extraction stages were extended from 5 (**LeNet**) to 7 to develop the applicability of CNN for diverse images' categories.

5.2 GoogleNet:

GoogleNet is used to handle high accuracy image recognition and classification CNNs tools, as it use 22 layers compared to **AlexNet** CNNs tool [40]. Googlenetis considered the new concept inception block for CNN, as it handles multi-scale convolutional transformations, so this enable it to encapsulate filtering images for different sizes (1x1, 3x3, and 5x5), and to capture spatial information at fine and coarse grain level, also **GoogleNet** convolutional layers are replaced with small similar to substituting each layer with micro NN which proposed by Network in Network (NIN) architecture [41]. Figure 9 shows neural networks Back propagation in general

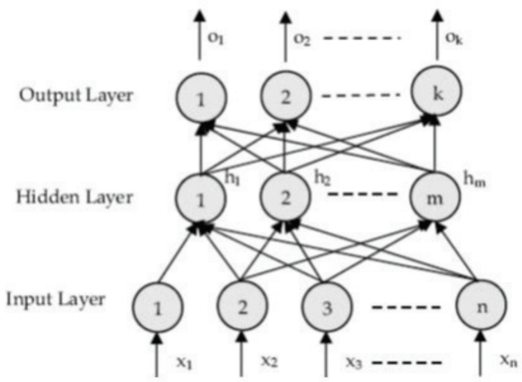

Figure 9: Neural networks back propagation

6 Trash Images Datasets

This research used a dataset repository that contains a large set of trash images [42]. The dataset contains six classes of images: glass, paper, cardboard, plastic, metal, and trash. Currently, the dataset consists of 2527 images which is a large dataset, the dataset is organized as shown in Table-1 follow:

Table 1: Distribution of Images in the Dataset

ImageType	**Glass**	**Paper**	**Cardboard**	**Plastic**	**Metal**	**Trash**
NO – Images	501	595	403	482	410	137

The pictures were taken by placing the object on a white poster board and using sunlight and/or room lighting to mimic the reality of waste trash materials. The pictures have been resized down to 512 x 384, which can be changed the size of the original dataset, 3.5GB, exceeds the git-lfs maximum size so it has been uploaded to Google Drive. Figure 10 shows the sample of data set that are printed using MATLAB tool before training CNNs.

7 Trash Images Datasets

Figure 10: Data set samples pictures

7.1 Experimental setup:

The main idea in this research is to investigate how trash waste material images can be classified using deep learning networks designed for normal object recognition in images. For this We ran the experiments on the PC containing 4GB of RAM, 4 Intel cores, i5 (2.0GHz each). Then we used MATLAB to implement the proposed model. An abstract should tell:

- Image detection by framing using binarization techniques.
- Image translation and thinning.
- Image detection by computing set of detection features.
- Image matching by matching two sets of detections to create a single set of image positions.

7.2 Result:

After CNNs classification tools are applied. AlexNet, and GoogleNet are selected to be used with a large dataset of trash images, and to compare the obtained results using the modified MATLAB tool. The obtained results for this large data showed that the accuracy result is 82%for GoogleNet, and 75% for AlexNet for the same number of iterations using the same infrastructure, while the Accuracy for AlexNet was 75% using the same dataset and infrastructure. The Time Results are 400, and 80 minutes for GoogleNet, and AlexNet respectively as shown in Table 2.

Table 2: Accuracy and time results at the same dataset

Category	**AlexNet**	**GoogleNet**
Accuracy	0.75	0.82
Times	80	400

More computation time has been pivotal factor in obtaining accurate results, when adding more layers feature extraction process. As an example, GoogleNet added 22 layers with 12 times fewer parameters than AlexNet, this enabled them to obtain higher accuracy, the more the computational time, the more the accuracy is. However, as AlexNet proved, with large datasets, same accuracy can be achieved with less computational time. **F1** score and recall are used as metrics to report accuracy using precision. Precision is calculated as the number of true positive detections divided by the total number of detections. While recall is calculated as the number of true positive detections divided by the total number of object labels. **F1** and **recall** are calculated using the equation below:

(**F1**) and (**RECALL**) are calculated using the equation below.

F1 = 2 * (precision.recall) / (precision * recall)

The results of **F1** and recall using (AlexNet and GoogleNet) are represented by table 3 as shown below:

Table 3: Recall, Precision and F1 results at the same dataset

Architecture	Recall	Precision	F1
AlexNe*t*	76	75	76
GoogleNet	83	82	83

From the results shown in table 3, we conclude that the results of GoogleNet are more accurate but need more time, so we recommend using **AlexNet** architecture; as consume less time in trash waste material images classification, then the classified material will be recycled later.

8 Conclusion and Future Work

Waste management is a vital issue, in one hand it can affect in economy growth since the waste management can reduce waste accumulation through the appropriate classification which open the ways of recycling and reusing of disposed materials. and in the other hand it can help positively to in reducing the pollution and producing healthy environment. In this paper we propose a complete semi smart adaptive approach for trash classification based on pre-recycling and post-recycling that utilize the new technologies and eliminating the human inferences by assigning a barcode and QR code for the materials to facilitate their separation as a pre-cycling post cycling, after the collection of trashes, an integrated automated separation approach is proposed to separate the garbage depending on the barcode and QR code, then ferrous and non-ferrous are separated using magnetic tape to isolate the metal materials from the others, soft and plastic materials are separated depending on their hardness using Durometer Hardness Test. convolutional neural networks are adopted to be used as an effective method to separate the trash images with a high accuracy using an effective approaches of Binarization, and Thinning. Matlab is modified and used to classify trash images reliable large data set using AlexNet and GoogleNet classifier models. The data set contains (501 glass, 594 paper, 403 cardboard, 482 plastic, 410 metal, and and137 trash images), the classifier models showed that GoogleNet classifier is superior to AlexNet with accuracy of 82%, but it needs more processing time, after the waste materials are separated recycling can be used to prevent pollution and utilize recycling benefits. We plan to do further smart investigation approaches such as deep fuzzy rule based and compare their results with what we obtained and implement smart solution in all the waste material management stages including waste gathering, transportation, classification, and recycling. In future works, the research plans to study further of smart investigation approaches such as deep fuzzy rule based and compare their results with what we obtained and implement smart solution in waste material management stages including waste gathering, transportation and classification. Regarding the recycling process the research plans to investigate more about smart pre-recycling algorithm as presented in Figure 11, to improve the initial classification process in a way to give a recycling percentage of waste materials.

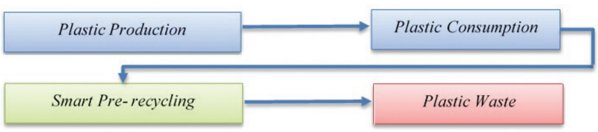

Figure 11: smart pre-recycling algorithm

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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